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MODELING HOME GROCERY DELIVERY USING ELECTRIC VEHICLES: PRELIMINARY RESULTS OF AN AGENT-BASED SIMULATION STUDY

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ABSTRACT

This paper presents preliminary results of an agent-based simulation study aimed at establishing whether a fleet of electric vans with different charging options can match the performance of a diesel fleet. We describe a base model imitating the operations of a real-world retailer using agents. We then introduce electric vehicles and charging hubs into our model. We evaluate how the use of electric vehicles, charging power and charging hubs influence the retailer's operations. Our simulation experiment suggests that, though they are useful, technological interventions alone are not sufficient to match the performance of a diesel fleet. Hence, reorganization of the urban delivery system is required in order to reduce carbon emissions significantly.

1 INTRODUCTION

Light goods vehicles (LGVs), representing 15% of the total vehicle mix (Department for Transport 2017), have contributed to approximately 16% of total UK greenhouse gas emissions from road transport (Department for Transport 2018b). Though the UK government's target of 100% new van sales of zero emissions by 2040 requires sales to grow consistently at a very high rate, uptake of battery electric vehicles (EVs) has remained low (Department for Transport 2018a). Within retail and parcel operations, this limited fleet penetration may be due to a multitude of factors, including range constraints (approximately 100 km for a typical electric LGV), 5% to 15% payload reduction due to battery weight, and higher cost of ownership.

This paper presents preliminary results from an ongoing project aimed at analyzing how the urban delivery system should be reorganized to enable the use of Electric LGVs, through an agent-based simulation (ABS) study centered on a home grocery delivery scenario based in Manchester, UK. The use of Electric LGVs is very important because significant decreases in carbon emissions cannot be achieved by using diesel vehicles. ABS is chosen as one of the approaches in this project because of the ill-defined nature of the problem, and the difficulty of isolating one element of the system from the others. For example, the changes in the retailer's performance will affect customers' perceptions, and eventually affect their behavior when placing orders to the retailer. In addition, an ill-defined problem can have many correct answers. Nowadays, ABS has been recognized as an appropriate approach to model human behaviors and to explore potential interventions to improve a system's performance.

In this paper, we first propose an ABS that can imitate the operations of one of the major home grocery retailers in the Manchester area. Iteratively, we introduce EVs and opportunity charging hubs into our modeling. Finally, we evaluate how these technologies influence the target retailer's operations and propose further modeling steps.

In Section 2 we present a literature review of previous ABS applications on EVs. This review aims to show that modeling commercial EVs is a novel area of application of ABS. In Section 3 we summarize a dataset provided by one of the major UK home delivery retailers, and subsequently in Section 3.1, we describe an ABS that behaves in a similar way to the retailer's ordinary operations. In Section 3.2 through 3.5 we introduce EVs and opportunity charging hubs into our modeling, and evaluate the impacts of these technologies on the retailer's operations. Finally, we discuss the conclusions of our study and suggest further research in Section 4.

2 LITERATURE REVIEW

ABS has been widely applied to study EVs. These studies can be broadly grouped into two groups: studies aimed at analyzing the adoption process for EVs, and studies aimed at analyzing how EVs interact with broader energy systems.

Within the first group, Eppstein et al. (2011) proposed a spatially explicit ABS that is able to explore the market penetration of private EVs. Their model considers spatial and social effects, as well as media influences. They used US consumers as a sample. Shafiei et al. (2012) proposed an ABS that can describe the evolution of market share of passenger vehicles in Iceland, including EVs. They took into account social influences and the attractiveness of the vehicle's attributes. Brown (2013) combined a mixed logistic regression model and ABS to simulate the diffusion of private EVs in the Boston metropolitan area. Propfe et al. (2013) simulated the penetration of EVs to the German passenger car market. They suggested that the market success of EVs depends on factors that include purchase price incentives, rising oil prices, and low energy costs for hydrogen and electricity. Querini and Benetto (2014) focused on the use of EVs to substitute passenger cars in Luxembourg. They analyzed the dynamics of EV adoption by combining ABS and life-cycle-analysis.

Within the second group, Lindgren and Lund (2015) used ABS to model electric passenger cars in Helsinki. Their objective was to identify potential bottlenecks in the utilization of shared charging hubs. Olivella-Rosell et al. (2015) studied the behaviors of EV users in Barcelona, Spain. Using ABS they simulated EV characteristics, user mobility needs, and charging processes required to reach their destination. Using this simulation they described how EV charging demands influence the electricity network. Tang et al. (2017) focused on finding potential charging locations that can minimize the total travel distance of passenger cars. They combined a non-deterministic polynomial model, ABS and ANOVA to identify these locations. They carried out a case study in Beijing. Farhan and Chen (2017) simulated a ride-sharing system using EVs in Austin, Texas. Their analysis suggests that this system may decrease private vehicle ownership, vehicle miles traveled, urban greenhouse gas emissions, and energy use. Finally, Latifi et al. (2019) proposed a scheduling process for EV charging aimed at minimizing the customers payments and maximizing the grid efficiency. Their ABS was developed based on a game theory concept.

This literature review shows that until recently ABS is mainly used to model passenger EVs. The novelty in this study is the application of ABS to model commercial EVs within a logistics system. Interaction in a logistics system tends to be more complex because it involves many diverse firms as well as consumers. To meet consumer needs, the firms must make many decisions including operational decisions, marketing decisions, and supply chain management decisions (Roorda et al. 2010). Unlike the private vehicle owners, a firm also needs to consider strategies for payload allocation, payload consolidation and vehicle routing (van Duin et al. 2012). In addition, this literature review also shows that case studies in the UK context are limited.

3 METHODOLOGY

We begin the modeling process by analyzing a set of real data for home grocery deliveries, recorded for 45 days between March and April 2017 in Manchester, provided by a major home delivery supplier in this area, referred to hereafter as the *target retailer*. From this data we identified several factors, including:

- The geographical distribution of the target retailer's customers;
- The order frequency and the quantity ordered by each customer;
- The distribution of delivery time window selected by the target retailer's customers;
- The location of the target retailer's stores (5 stores);
- The number of vehicles available at each store (all diesel vehicles);
- The total number of vehicles operated by the target retailer (18 vans);
- The number of journeys of each vehicle and the drop density in each journey.

In Section 3.1 we present an ABS that aims to imitate the target retailer's operations. We use the factors mentioned above to parametrize our simulation. This simulation is implemented using AnyLogic® version 8.3, and is implemented with 30 minute time intervals.

3.1 ABS of a Fleet Consisting of Diesel Vehicles (Base Model)

We define three types of agents in our ABS: the retailer agent, the store agents and the vehicle agents. In order to set up the simulation in AnyLogic®, the agent locations are added to a GIS layer obtained from OpenStreetMap (OpenStreetMap 2019), while the road network data providing inter-point distances and topology is obtained from the open data set provided online by Geofabrik GmbH (Geofabrik 2019).

Each day in the simulation starts by randomly generating orders from the provided data. The first step is to generate the desired quantity of orders for each day, which is achieved by sampling a normal distribution with parameters ($\mu = 115.43, \sigma = 32.9$) in accordance with daily order statistics from the target retailer data and rounding to the nearest whole number. Each of these orders is then assigned to a random customer based on the dataset's empirical distribution of each customer's order frequency. The delivery time window is then similarly determined using the empirical distribution of time windows for the selected customer. Table 1 illustrates a toy example consisting of four different customer locations and two possible delivery windows.

Table 1: Example of customer order data.

Customer ID	Orders in data	Morning orders	Evening orders
1	3	1	2
2	13	4	7
3	8	7	0
4	10	5	5

In this example, when an order is generated, its location is selected as customer 1 with probability 3/34, customer 2 with probability 13/34, etc. If customer 2 is selected, the delivery window will then be selected as morning with probability 4/11 and evening with probability 7/11. The deployed algorithm functions in a similar manner, using 14 time windows instead.

Each order can consist of three categories of product: ambient, chilled and frozen. For each order, the quantity of each product category is determined by sampling a normal distribution and rounding to the nearest whole number, using parameters as follows:

- ambient products ($\mu = 3.0, \sigma = 1.23$)
- chilled products ($\mu = 1.16, \sigma = 0.48$)
- frozen products ($\mu = 0.62, \sigma = 0.51$)

For each order, the retailer agent selects one of its stores to serve it. The selection process is based on the proximity between the store agent and the customer's location (Delaney-Klinger et al. 2003), based on the route that will be chosen by the vehicle when delivering the order. This is determined through the use of Dijkstra's Shortest Path algorithm (Cherkassky et al. 1996) operating on the Geofabrik road network dataset. This algorithm selection was purely empirical i.e., it produced the smallest error when the calculation result was compared to the data provided by the target retailer. To validate this process we compare the store selected by the retailer agent to the store selected by the target retailer for each customer in the dataset. Our comparison shows that 88% of the times our simulation can predict which store that is selected by the target retailer. This level of accuracy shows that the validity of this process is sufficiently high, but it also indicates that there are other factors that are considered by the target retailers to select which stores that should serve orders.

The next step to simulate is the grouping of orders into several vehicle journeys. In reality, the target retailer uses commercial software to carry out this process. Due to business confidentiality, we do not know how exactly this commercial software works. However, at this research phase we are only aiming at establishing a system that has some resemblances to the target retailer's operations and not to propose a more efficient routing algorithm. Hence in our simulation, we rely on heuristics to obtain feasible solutions. Our heuristics is a modification of Nearest Neighbor heuristics, as explained by for example by Balakrishnan (1993). The main difference is that we use a scoring system to evaluate the payoff from including a customer into a vehicle's journey. The following pseudocode explains the heuristics in our simulation.

```
PROCEDURE AssignVehicleJourney (NumOrder, NumVehicle):
    get OrderSize[NumOrder]; get DeliveryWindow[NumOrder];
    sort OrderSize based on DeliveryWindow (ascending);
    FOR i IN 1 TO NumVehicle
        PlanLocation[i] = store; Capacity[i] = 108;
        PlanArrival[i] = SimulationTime;
        PlanDeparture[i] = SimulationTime;
        JourneyTime[i] = 0; Destination[i] = [];
    ENDFOR;
    FOR j IN 1 TO NumOrder DO
        Real TotalScore [NumVehicle];
        FOR k IN 1 TO NumVehicle DO
            IF (Capacity[k] >= OrderSize[j] AND
            JourneyTime[k] < 4.5) THEN
                calculate Distance from PlanLocation[k] to
                Customer[j];
                calculate TravelTime between PlanLocation[k]
                to Customer[j];
                TotalScore[k] = ScoreDistance + ScoreArrival;
            ENDIF;
        ENDFOR;
        //get vehicle with the highest score
        m = index(max(TotalScore));
        PlanLocation[m] = Customer[j];
        PlanArrival[m] = PlanDeparture[m] + TravelTime;
        PlanDeparture[m] = PlanArrival[m] + DwellTime;
        //DwellTime is 7 minutes
        JourneyTime[m] = JourneyTime[m] + TravelTime + DwellTime;
        Capacity[m] = Capacity[m] - OrderSize[j];
        //Add customer j to vehicle m's destination list
        Destination[m][size(Destination[m])+ 1] = Customer[j];
    ENDFOR;
END.
```

The first step in our heuristic is to filter which vehicles are capable to carry orders from a particular customer. There are two criteria used in this filtering process:

- **Vehicle capacity:** According to a source from the target retailer, each vehicle can carry up to 108 crates. Two-thirds of the vehicle's capacity is allocated for ambient crates. The rest is allocated for chilled and frozen crates.
- **Total journey time:** Health and safety regulations require a driver to take a break after driving for 4.5 hours (Driver & Vehicle Standard Agency 2014). Therefore, as a simplification, we assume that the vehicle must return to the store within 4.5 hours.

Of all capable vehicles, our heuristic method selects which vehicles will deliver an order from a particular customer using a scoring system. This scoring system considers two factors:

- **Punctuality:** We consider whether the vehicle can arrive within the delivery time window selected by the customer. A vehicle gets a score of 100 if it can arrive within the delivery time window selected by the customer, and gets a smaller score if it arrives too early or too late.
- **Distance:** The distance from the vehicle's last location to the customer's location. The arrival time is obtained by adding the time required to reach the customer's location, to the planned departure time of the vehicle from its last location. In calculating this travel time, we assume that all vehicles move at a same and constant speed. Based on UK Department for Transport data, the average vehicle speed around Manchester area in 2017 is 30.57 km / hour (Department for Transport statistics 2017). A vehicle's score is calculated relative to the distance of other vehicles to the customer's location. The closest vehicle to the customer's location gets a score of 100 while the furthest vehicle gets a score of 0. The order is then incorporated to the destination list of the vehicle with the highest total score.

The vehicle agents then deliver the customers' orders according to their destination list. In this model version we assume that there is no interaction between vehicles and traffic conditions. Therefore the vehicle will always arrive at each destination as planned.

For validation, we ran our base model for 45 simulation days, with the whole simulation then repeated seven times. Table 2 shows the comparison between our simulation's outputs to the real data.

Table 2: Comparison between the base model outputs to the real data.

Output Variables	Real Data Average	Real Data Std.Dev	Simulation Average	Simulation Std.Dev
Number of orders per day (crates)	115.43	32.9	117.34	4.21
Number of Ambient Crates	346.31	104.7	351.12	12.25
Number of Chilled Crates	133.59	40.63	135.53	5.39
Number of Frozen Crates	72.09	22.58	73.32	2.46
Vehicles dispatched per day	23.75	3.81	24.26	0.62
Drop density (deliveries / journey)	4.86	2.58	4.9	0.1
Distance per journey (km)	49.20	28.74	50.21	3.67
Time travelled per journey (hours)	1.51	0.9	2.34	1.09

With this small number of replications, the statistical power to carry out a hypothesis testing will be very low. However, descriptively we can observe that the retailer agent in the simulation carries out similar daily operations to the target retailer. Therefore, there can be a reasonable expectation that an intervention introduced to the retailer agents, such as incorporation of EVs, will influence the target retailer in a similar manner.

3.2 Incorporating Electric Vehicles into the ABS

Characteristics that distinguish an EV from its diesel counterpart are, principally, its limited range and the substantial time required to charge its battery pack. In addition, unlike a tank of diesel, the vehicle's battery will typically not be fully utilized; to maintain its lifetime, best practice requires a battery pack to be maintained so that remaining power never falls below 20% of its capacity. To capture these constraints we added several attributes to vehicle agents in our ABS. These attributes are:

- Battery capacity (kWh): Power that can be stored in the vehicle's battery.
- Motive power consumption (kWh/km): The amount of power spent on each kilometer travelled by the vehicle.
- Refrigeration unit power consumption (W/h): The amount of power consumed by the vehicle's refrigeration unit per hour.

We then modified the heuristics described in Section 3.1. The following pseudocode describes the modifications that we introduced to the base model. This modification aims to ensure that the vehicle returns to its store with at least 20% of its battery capacity.

```
PROCEDURE AssignVehicleJourney (NumOrder, NumVehicle):
    ...// continue as explained in Section 3.1
    FOR i IN 1 TO NumVehicle
        Battery[i] = 56; //Battery capacity
        ...// continue as explained in Section 3.1
    ENDFOR;
    FOR j IN 1 TO NumOrder DO
        Real TotalScore [NumVehicle];
        FOR k IN 1 TO NumVehicle DO
             ...// continue as explained in Section 3.1
            Calculate PowerRequired to go to Customer[j]
            and return to the store;
            IF (Capacity[k] >= OrderSize[j] AND
            JourneyTime[k] < 4.5 AND
            (Battery[k] - PowerRequired) >= 0.2 * 56 )
            THEN TotalScore[k] = ScoreDistance + ScoreArrival;
            ENDIF;
        ENDFOR;
        m = index(max(TotalScore));
        Battery[m] = Battery[m] - PowerRequired;
        ...// continue as explained in Section 3.1
    ENDFOR;
END.
```

3.3 Effect of Charger Selection on Feasibility of Electric Vehicles in the ABS

In this section we analyze the effects of the charger power to the feasibility of EV. We assume that the vehicles are only charged at the store. When batteries are being charged, the rate at which battery power increases depends on the charger power used by the retailer, and this should be reflected in the retailer agent in the ABS to ensure that lead times to operation of a vehicle with depleted energy can be modeled correctly.

There are several types of electric vans available in the current market. Of all these van types, the van with characteristics similar to those of the target retailer has a battery pack capacity of 56 kWh, power consumption of 0.29 kWh/km and refrigeration unit power consumption of 500W. With regards to the charger, there are two main types of charger currently in use for these purposes: namely, dedicated AC charging systems with 3 kW power, and DC charging systems with 22kW power.

We carry out experiments to evaluate changes in the retailer agent's capability to deliver the order, assuming it operates vehicles with the above characteristics. This capability is measured by the percentage of timely delivery, from all orders generated in one day, using the same number of vehicles. There are three scenarios in these experiments:

- Scenario 1: All of the retailer agent's vehicles are diesel.
- Scenario 2: All of the retailer agent's vehicles are electric and the retailer uses 3kW chargers.
- Scenario 3: All of the vehicles are electric and the retailer uses 22kW chargers.

As the retailer agent has only 18 vehicles, in order to serve all of the orders, sometimes one vehicle is used more than once in one day; as this will involve a charging period for electric vans, we therefore expect in these cases that charging times will become significant in the retailer agent's ability to fulfil the generated orders.

Each scenario is run for 100 simulated days. We control the simulation's random seed value so that the orders generated in each scenario are the same. Controlling the random seed is also a way to improve the reproducibility of our experiments (i.e., when the same program is run using the same inputs, the results from two experiments with the same random seed will be similar). To measure the retailer agent's capability, we recorded two output variables: the percentage of orders that can be delivered in timely manner from all orders generated on each day, and the average number of vehicles that can be dispatched on each day. A delivery is considered to be untimely if the van arrives after the customer's delivery window is ended. Table 3 describes the outputs produced by each scenario.

Table 3: The retailer agent's capability to deliver customers' orders under different scenarios.

Output Variable	Scenario 1 (Diesel)	Scenario 2 (3kW)	Scenario 3 (22 kW)
Percentage of timely delivery (%)	100%	43%	72%
Average number of vehicles dispatched per day (vans / day)	18.4	17.34	18.04

Table 3 shows that, when only diesel vehicles are used, the retailer agent can deliver all of the orders it received in a timely manner, which is an expected result as there are no constraints based on charging times. However, Table 3 also shows that the percentage of timely deliveries possible with scenarios 2 and 3 are significantly lower; with the same number of vehicles. Note that in scenarios 2 and 3, the retailer agent is still able to satisfy the same number of orders, however it is more difficult to do it in a timely manner due to the range and charging considerations. The fact that the retailer agents can still deliver the same number of orders in scenarios 2 and 3 indicates that there is still quite a lot of slack in the target retailer's diesel fleet operations.

By comparing scenario 2 and scenario 3, it can be concluded that the charger's power will affect the retailer agent's capability to deliver the orders. Higher-powered chargers help the retailer agent to dispatch the vehicles more frequently, and thus deliver the orders in a more timely manner with the same fleet size.

3.4 Identifying Potential Locations of Charging Hubs

Enabling the vehicle to undertake *opportunity charging* may increase the retailer agent's capability to deliver the order. Opportunity charging describes the scenario where charging hubs are present at locations other than the home retailer stores, and thus allow electric vans to charge while on their delivery round. To incorporate charging hubs in our model, first potential locations to place these charging hubs must be identified. Potential locations must be accessible by as many vehicles as possible at the point where their batteries are too low to serve any further orders; this will ensure that diversionary distances are minimized when a vehicle needs to charge.

To identify these potential locations, first we recorded the *last planned location* (LPL) of each vehicle in scenario 2 and scenario 3. The LPL indicates the location where a vehicle stopped serving more orders and needed to return to its home store to charge; the hypothesis is that, if there are charging hubs that can be reached from its LPL, then the vehicle could potentially use these instead and therefore be able to serve more orders. We also recorded the vehicle's remaining battery power at these locations, indicating the remaining range of the vehicle.

There are 2424 customer locations in the data provided by the target retailer. Out of these, 1840 locations occur at some points as a vehicle's LPL. We count how many times a particular location becomes the vehicles' LPL. This frequency is equivalent to the volume of demand in the particular location. We also calculate the average value of these vehicles' remaining range at each LPL. Figure 1 shows an example. LPLs that are close to the target retailer's store are eliminated, as the likelihood that vehicles cannot reach the store from these locations is very small. In this elimination process a LPL was retained if the distance to the store is shorter than the average remaining range of the vehicles at the given LPL. Because the target retailer's stores are located near the city center, this rule means that remaining potential charging hub locations are located in the suburbs.

	A	B	D	F
1	**Lat**	**Lon**	**Frequency**	**Avg Rem Battery**
2	53.4xxxxx	-2.0xxxxx	18	5.776418235
3	53.3xxxxx	-1.9xxxxx	17	11.0168232
4	53.3xxxxx	-2.2xxxxx	17	9.19113983
5	53.4xxxxx	-2.3xxxxx	16	5.27031451
6	53.5xxxxx	-2.2xxxxx	15	7.445934353

Figure 1: Data extracted from the simulation to identify potential charging hub locations.

We applied multiple center of gravity concepts (Drezner and Drezner 2006) to the remaining locations to find potential charging hub locations. We began by calculating a center of gravity from all LPLs. Then we measured whether this center of gravity can be reached from all LPLs given the average remaining battery at each LPL. If this is not the case, then we increased the number of potential locations in our model. These new locations are initially assigned to the farthest LPLs from the initial center of gravity. The initial center of gravity was then deleted. The remaining LPLs are then clustered to the nearest potential location. A new center of gravity was then calculated for each cluster. We repeated this procedure until the vehicle can reach at least one center of gravity regardless its LPL. Figure 2 describes this process in more detail. Using this concept we found two centers of gravity that can be reached from all other locations.

3.5 Incorporating Charging Hubs into the ABS

To evaluate the benefits of charging hubs to the retailer agent's operations, we define a new type of agent in our ABS, namely, the charging hub agent. The locations of these agents are initiated based on the location proposed in Section 3.4. The number of vehicles that can be served by the charging hub agents at a time is assumed to be unlimited.

To incorporate the charging hubs into our ABS, we assume that every time an order is allocated to one vehicle, all of the vehicles evaluate their remaining battery power. In this evaluation process they calculate the power required to reach the nearest customer location, from all of the unallocated orders, and return to their store. If a vehicle cannot reach the nearest customer location, then it will not be able to carry more

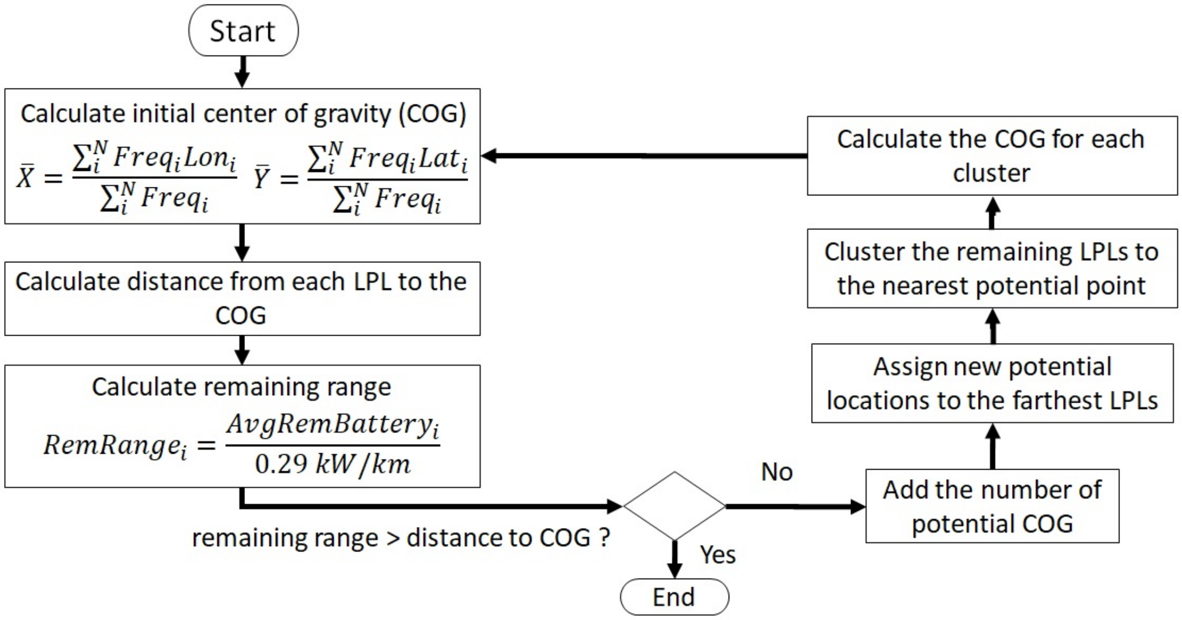

Figure 2: The process to find potential charging locations using the center of gravity concept.

orders without charging its battery at the store or at one of the charging hubs. Therefore we modified the pseudocode in Section 3.2 as follows.

```
PROCEDURE AssignVehicleJourney (NumOrder, NumVehicle):
    ...// continue as explained in Section 3.2
    FOR j IN 1 TO NumOrder DO
        Real TotalScore [NumVehicle];
        FOR k IN 1 TO NumVehicle DO
            ...// continue as explained in Section 3.2
        ENDFOR;
        m = index(max(TotalScore));
        ...// continue as explained in Section 3.2
        FOR n IN 1 TO NumVehicle DO
            Calculate PowerRequired to go to the closest Customer
            and return to the store;
            IF (Battery[n] <= PowerRequired) THEN
                Go to the nearest charging hub or return to
                the store;
            ENDIF;
        ENDFOR;
    ENDFOR;
END.
```

We assume that the vehicle agent will spend two hours each time it visits a charging hub or returns to the store to recharge. To evaluate the benefits of incorporating charging hubs we define two additional scenarios:

- Scenario 2A: There are two charging hubs, and both the store agents and the charging hubs are equipped with 3kW chargers.
- Scenario 3A: As per Scenario 2A, but store agents and charging hubs use 22kW chargers.

Each scenario uses the same random seed as the experiments in Section 3.2, ensuring the number of orders received by the retailer agent is the same as that in scenario 1. Once again, each scenario is run for 100 simulated days. Table 4 presents the percentage of timely deliveries and the number of vehicles that can be dispatched per day in these two updated scenarios.

Table 4: The benefits of incorporating charging hubs into the retailer agent's operations.

Output Variable	Scenario 2A (2 charging hubs, 3kW power)	Scenario 3A (2 charging hubs, 22kW power)
Percentage of timely delivery (%)	59%	88%
The average number of vehicles dispatched per day (vans / day)	17.1	17.4

Table 4 shows the percentage of timely deliveries in Scenarios 2A and 3A are higher than those in Scenarios 2 and 3 respectively. This indicates that the existence of charging hubs can help the retailer agent improve its performance without increasing its fleet size. The average number of vehicles dispatched per day in scenarios 2A and 3A are slightly lower than those in scenarios 2 and 3; this is because the vehicles can be charged without returning to their store. However, a fleet consisting of EVs cannot match the performance of a fleet consisting of diesel vehicles even by use of charging hubs.

4 CONCLUSIONS, LIMITATIONS, AND FURTHER RESEARCH

4.1 Conclusions

In this study we have proposed an ABS model of home grocery delivery performed by a fleet consisting of diesel vehicles, and used its results as a baseline from which to predict the effect of replacing diesel vehicles with electric vans in a range of charging scenarios.

We showed that a descriptive statistics comparison suggests that the retailer agent in our simulation can operate in a way that produces very similar results to the real data provided by the target retailer.

When we introduce EVs, the fleet can still deliver the same number of orders, without adding the number of vehicles. This indicates that there are still quite a lot of slack in the target retailer's diesel fleet operations. However, using EVs, both with and without charging hubs, is very likely that the fleet cannot satisfy the delivery time window. This is due to the time required to charge the vehicles. Nevertheless, we showed that the use of opportunistic charging hubs could help to improve the performance of an EVs fleet, by reducing the need for out-of-charge vehicles to return to their home stores. In addition, we showed that using more powerful chargers can significantly increase the percentage of timely delivery that can be done by the retailer agent using electric vans.

To maintain its punctuality performance, one of the alternatives that can be chosen by an operator is to increase the number of their vans. Another alternative is to operate more charging hubs so that the vans can be charged closer to the customer locations, if needed. If the retailer is unable to operate more electric vans or charging hubs, then they can try to negotiate the delivery time window with their customers (e.g., by offering a wider delivery time window, or by giving discount for each late delivery). However, understanding how the customers respond the changes in the target retailer's performance and these interventions require us to establish behavioral models of the customers. Modeling the dynamics of the relationship between a retailer and their customers is also an important topic beyond the scope of this project, for example for agri-food supply chain studies (Utomo et al. 2018).

Although possible technological interventions exist, they can be very expensive or risky to be carried out unilaterally by an operator. Hence, in order to reduce carbon emissions at an reasonable cost, the urban delivery system must be reorganized. This reorganization process may require different fleet operators to operate more experimental strategies, such as collaboration or synchronization of order fulfillment.

4.2 Limitations

The first limitation in this study is related to the number of replication and the level of order used in our experiments. Because of the low number of replications, the experiment outputs do not have sufficient statistical power to estimate system performance in reality. Therefore we are working to improve the efficiency of our model, so that we can produce more replication in a relatively short time. In addition, the level of orders in our experiments were also constrained within the range of data provided by the target retailer. To test the robustness of the interventions proposed from this study, a sensitivity analysis with different levels of order is required.

The second limitation of this research is our assumption regarding the vehicle's capacity. Here we assumed that the vehicle's capacity can solely be measured based on the number of crates. Whereas the capacity involves two dimensions, namely the volume (crates) and the total weight. We used this assumption because the weight of each order is not specified in our dataset.

The third limitation is related to the methodology we use to identify potential locations for charging hubs. We acknowledge that many methods that can propose more optimal solutions are available. At this research phase we chose this simple framework because it is relatively easy to verify and to communicate with the stakeholders who are involved in our project. Nevertheless, even by using this simple framework we have successfully demonstrated the potential benefits of these charging hubs.

4.3 Further Research

One of the further pieces of research that will be carried out is to incorporate multiple fleets in our simulation. We can evaluate the benefits and the costs if each fleet operates its own charging hubs. We can also evaluate the benefits and costs if they were to use the same set of charging hubs. If the latter case is more beneficial, then it may show potential advantages to be gained for fleet operators if they were to organize such a co-operative system. When a set of charging hubs are shared by multiple fleets of electric vans, we then need to design and propose the scheduling schemes to use these facilities. Sensitivity analysis using various combinations of technologies and demand pattern is required to propose a robust solution.

Another further research subject may be to consider uncertainties in our modeling. In this model we assume that the vehicles can move at constant speed because they do not interact with the traffic conditions. If they interact with the traffic conditions then their speed will be dynamic and planned deliveries may not always be fulfilled; these issues are important to consider in the payloads and routes allocation process.

Finally, we are also working on incorporating better payload and routing algorithms in our modeling. Many algorithms have been proven to be able to minimize the distance traveled by the vehicles and optimizing vehicle utilization. Some of these routing algorithms are specially designed for electric vehicles (see Pelletier et al. 2016 for a detailed review). Incorporating these algorithms may improve the feasibility of the electric vehicle deployment.

REFERENCES

Balakrishnan, N. 1993. "Simple Heuristics for the Vehicle Routing Problem with Soft Time Windows". *Journal of the Operational Research Society* 44:279–287.

Brown, M. 2013. "Catching the PHEVer: Simulating Electric Vehicle Diffusion With an Agent-based Mixed Logit Model of Vehicle Choice". *Journal of Artificial Societies and Social Simulation* 16(2):5.

Cherkassky, B. V., A. V. Goldberg, and T. Radzik. 1996. "Shortest Paths Algorithms: Theory and Experimental Evaluation". *Mathematical Programming* 73(2):129–174.

Delaney-Klinger, K., K. Boyer, and M. Frohlich. 2003. "The Return of Online Grocery Shopping: A Comparative Analysis of Webvan and Tesco's Operational Methods". *The TQM Magazine* 15(3):187–196.

Department for Transport 2017. "Road Traffic Estimates: Great Britain 2017". Technical report. London: Department for Transport.

Department for Transport 2018a. "The Road to Zero: Next Steps Towards Cleaner Road Transport and Delivering Our Industrial Strategy". Technical report. London: Department for Transport.

Department for Transport 2018b. "Transport Statistics Great Britain 2018". Technical report. London: Department for Transport.

Department for Transport statistics 2017. "DfT Travel Time Data". https://www.gov.uk/government/organisations/department-for-transport/series/road-congestion-and-reliability-statistics.

Drezner, T. and Z. Drezner. 2006. "Multiple Facilities Location in the Plane Using the Gravity Model". *Geographical Analysis* 38(4):391–406.

Driver & Vehicle Standard Agency 2014. "Staying Legal". https://www.gov.uk/government/publications/staying-legal-heavy-goods-vehicle-drivers.

Eppstein, M. J., D. K. Grover, J. S. Marshall, and D. M. Rizzo. 2011. "An Agent-based Model to Study Market Penetration of Plug-in Hybrid Electric Vehicles". *Energy Policy* 39(6):3789–3802.

Farhan, J. and T. D. Chen. 2017. "Impact of Ridesharing on Operational Efficiency of Shared Autonomous Electric Vehicle Fleet". *Transportation Research Part C* 93:310–321.

Geofabrik 2019. "OpenStreetMap Data Extracts". www.http://download.geofabrik.de/.

Latifi, M., A. Rastegarnia, A. Khalili, and S. Sanei. 2019. "Agent-based Decentralized Optimal Charging Strategy for Plug-in Electric Vehicles". *IEEE Transactions on Industrial Electronics* 66(5):3668–3680.

Lindgren, J. and P. D. Lund. 2015. "Identifying Bottlenecks in Charging Infrastructure of Plug-in Hybrid Electric Vehicles Through Agent-based Traffic Simulation". *International Journal of Low-Carbon Technologies* 10(2):110–118.

Olivella-Rosell, P., R. Villafafila-Robles, A. Sumper, and J. Bergas-Jane. 2015. "Probabilistic Agent-based Model of Electric Vehicle Charging Demand to Analyse the Impact on Distribution Networks". *Energies* 8(5):4160–4187.

OpenStreetMap 2019. "Planet OSM". https://www.openstreetmap.org, accessed 23rd August.

Pelletier, S., O. Jabali, and G. Laporte. 2016. "50th Anniversary Invited Article—Goods Distribution with Electric Vehicles: Review and Research Perspectives". *Transportation Science* 50:3–22.

Propfe, B., D. Kreyenberg, J. Wind, and S. Schmid. 2013. "Market Penetration Analysis of Electric Vehicles in the German Passenger Car Market Towards 2030". *International Journal of Hydrogen Energy* 38(13):5201–5208.

Querini, F. and E. Benetto. 2014. "Agent-based Modelling for Assessing Hybrid and Electric Cars Deployment Policies in Luxembourg and Lorraine". *Transportation Research Part A* 70:149–161.

Roorda, M. J., R. Cavalcante, S. McCabe, and H. Kwan. 2010. "A Conceptual Framework for Agent-based Modelling of Logistics Services". *Transportation Research Part E: Logistics and Transportation Review* 46(1):18–31.

Shafiei, E., H. Thorkelsson, E. I. Asgeirsson, B. Davidsdottir, M. Raberto, and H. Stefansson. 2012. "An Agent-based Modeling Approach to Predict the Evolution of Market Share of Electric Vehicles: A Case Study from Iceland". *Technological Forecasting & Social Change* 79(9):1638–1653.

Tang, M., D. Gong, S. Liu, and X. Lu. 2017. "Finding Key Factors Affecting the Locations of Electric Vehicle Charging Stations: A Simulation and ANOVA Approach". *International Journal of Simulation Modelling (IJSIMM)* 16(3):541–554.

Utomo, D. S., B. S. Onggo, and S. Eldridge. 2018. "Applications of Agent-based Modelling and Simulation in the Agri-food Supply Chains". *European Journal of Operational Research* 269:794–805.

van Duin, J. R., A. van Kolck, N. Anand, and E. Taniguchi. 2012. "Towards an Agent-based Modelling Approach for the Evaluation of Dynamic Usage of Urban Distribution Centres". *Procedia-Social and Behavioral Sciences* 39:333–348.

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